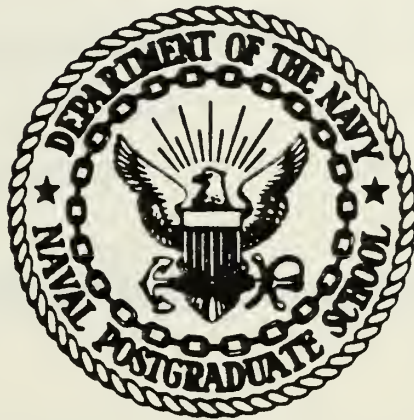


INVESTIGATION OF PARAMETERS AFFECTING
VOICE RECOGNITION SYSTEMS IN C3 SYSTEMS

Mary Pamela Batchellor

NAVAL POSTGRADUATE SCHOOL

Monterey, California



THESIS

INVESTIGATION OF PARAMETERS AFFECTING
VOICE RECOGNITION SYSTEMS IN C3 SYSTEMS

by

Mary Pamela Batchellor

March 1981

Thesis Advisor:

G. K. Poock

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- the adaptability of a random sample of active duty military personnel to a voice input system.
- the accuracy of such a system.
- the effects of male versus female operators.
- the effects of officer versus enlisted operators -- the advantages/disadvantages of using three, five or ten trained passes to train the voice system.

Results showed no significant difference in error rates between the categories of officer and enlisted nor between male and female. Three training passes had a slightly higher error rate than five or ten passes but five and ten passes were the same.

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Investigation of Parameters Affecting
Voice Recognition Systems in C3 Systems

by

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Lieutenant Commander, United States Navy
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Submitted in partial fulfillment of the
requirements for the degree of

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from the

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March 1981

ABSTRACT

This research investigates the use of a voice recognition system by military operators -- officer, enlisted, male and female. The application intended is the use of a discrete utterance voice recognition system in a command center environment. The system would be used by members of a watch team to execute ad hoc queries against an automated data base in support of their command center duties. The following factors were examined:

- the adaptability of a random sample of active duty military personnel to a voice input system.
- the accuracy of such a system.
- the effects of male versus female operators.
- the effects of officer versus enlisted operators.
- the advantages/disadvantages of using three, five or ten training passes to train the voice system.

Results showed no significant difference in error rates between the categories of officer and enlisted nor between male and female. Three training passes had a slightly higher error rate than five or ten passes but five and ten passes were the same.

TABLE OF CONTENTS

I.	INTRODUCTION-	- - - - -	9
A.	BACKGROUND-	- - - - -	9
	1. Voice Technology-	- - - - -	9
	2. Command, Control and Communications - - -		13
B.	OBJECTIVES-	- - - - -	16
II.	METHOD-	- - - - -	18
A.	DESIGN-	- - - - -	18
B.	SUBJECTS-	- - - - -	18
C.	EQUIPMENT - - - - -		20
D.	PROCEDURE - - - - -		24
E.	DEPENDENT VARIABLES - - - - -		25
III.	ANALYSIS AND RESULTS-	- - - - -	27
A.	HYPOTHESES-	- - - - -	27
B.	RESULTS FOR SEX - - - - -		27
C.	RESULTS FOR RANK -- OFFICER VS. ENLISTED- - -		30
D.	RESULTS FOR NUMBER OF TRAINING PASSES -- 3, 5, 10- - - - -		32
E.	RESULTS FOR NUMBER OF UTTERANCE SYLLABLES -- 1, 2, 3, 4, 5 - - - - -		38
IV.	DISCUSSION AND CONCLUSIONS-	- - - - -	43
APPENDIX A.	SUBJECT QUESTIONNAIRE AND ANSWER SHEET - - - - -		45
APPENDIX B.	INSTRUCTIONS TO SUBJECTS - - - - -		48
APPENDIX C.	VOCABULARY - - - - -		50
APPENDIX D.	CONFUSION MATRIX - - - - -		51

LIST OF REFERENCES- - - - - 52

INITIAL DISTRIBUTION LIST - - - - - 53

LIST OF FIGURES

1.	Conceptual Design of Experiment - - - - -	19
2.	Equipment Set-Up- - - - -	21
3.	Graph for Errors vs. SEX- - - - -	28
4.	Graph for Errors vs. RANK - - - - -	31
5.	Graph for Number of Training Passes vs. Rank- - - -	33
6.	Graph for Number of Training Passes vs. Sex - - - -	34
7.	Graph for Number of Training Passes vs. Order of Training - - - - -	37
8.	Graph for Errors vs. Number of Syllables for Three Training Passes - - - - -	39
9.	Graph for Errors vs. Number of Syllables for Five Training Passes- - - - -	40
10.	Graph for Errors vs. Number of Syllables for Ten Training Passes - - - - -	41

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I. INTRODUCTION

A. BACKGROUND

1. Voice Technology

"It is only a matter of time until automatic speech recognition (ASR) becomes a major force in man-machine communication because of the inherent advantages of speech communication and our increasing need to communicate with machines. The inherent advantages of speech arise from its universality, convenience, and speed." [Ref. 1].

Speech is the human's fastest and most convenient method of communicating and consequently little or no operator training is required if speech is used as the interface between man and computer. In experiments involving speech and other forms of machine communication (e.g., typing), information is exchanged almost twice as fast with speech [Ref. 2]. In addition to the speed and ease of training, speech input frees the operators' hands and eyes for other tasks [Ref. 3].

The use of voice input to machines can be categorized into three modes of operation:

- voice response.
- speaker verification.
- speech recognition.

VOICE RESPONSE is the area of voice input which deals with speech synthesis -- voice readout of computer-stored data. The appropriate message is selected from a stored

vocabulary by a synthesis program and then given to a synthesizer device which generates a signal for transmission over a voice circuit [Ref. 4].

SPEAKER VERIFICATION involves authenticating the identity of a speaker according to measurements on his voice signal. Applications for speaker verification systems include voice lock/unlock security systems and banking and credit transaction [Ref. 5].

SPEECH RECOGNITION is giving commands to machines by voice. The machine does not have to identify the speaker, only "recognize" what is said. The commands can be given by any speaker as long as his or her voice patterns match those parameters for the desired stored command. Speech recognition systems are used for baggage and parcel sorting, quality control on production lines and voice direction of machine tools. They are typified by small word vocabularies spoken by a small population of users or large vocabularies (several hundred words) for speakers who allow the machine to calibrate their voices [Ref. 6].

The first experiments with speech input to machines were done in the 1950's using vowel and digit recognition systems. Today there are commercially available isolated word recognition systems which easily handle small vocabularies from a known set of speakers. Actual systems in use today include United Air Lines baggage handling system, Ford

Motor Company's assembly line inspection of cars and Union Carbide's nuclear products manipulation system at Oak Ridge and Lockheed's quality control inspection line in Sunnyvale, California.

There are two features which characterize the complexity of the speech recognition task:

- whether the speech is connected or spoken one word at a time.
- the size of the vocabulary.

In connected speech the acoustic characteristics of sounds and words have greater variability. In addition, it is difficult to determine where one word ends and the next begins. As the number of words in the vocabulary and the number of different contextual variations per word increase, the storage required to store all reference patterns becomes enormous.

The principal difficulty in automatic speech recognition is not due to a lack of speech understanding but to the massive amount of memory and time required to store and process the required data. Recent progress has been limited more by advances in data processing than in speech recognition technology [Ref. 7].

Therefore, a major disadvantage of speech recognition systems is the requirement for large amounts of memory and processing time. Some additional problems are:

- speaker variability due to sex and dialect makes recognition very difficult.

- speech communication is not private.
- speech communication may be subject to environmental noise and distortions.
- voice input is expensive in comparison to other input/output devices. (The cost of voice input devices ranges from \$200 to \$80,000 which includes a wide variety of capabilities.)

In spite of these restrictions, applications for voice systems today include several areas:

- a. voice readout of numerals.
 - (1) telephone numbers.
 - (2) assembly of equipment.
 - (3) stock price quotations.
 - (4) inventory reporting.
 - (5) automatic directory assistance.
- b. industrial applications.
 - (1) special purpose computer programming for machine tools.
 - (2) quality control inspection systems.
 - (3) equipment handling and sorting systems.
- c. editing of financial information.

This thesis will address another application for today's voice recognition systems -- that of command and control. The implication here is not command and control in the sense of voice communication with machines but in the military application of a management information system which provides data on resources available.

2. Command, Control and Communications (C3)

In 1972 the Honeywell 6000 computer (H6000) was installed at Commander in Chief Naval Forces Europe (CINCUSNAVEUR) in support of the World Wide Military Command and Control System (WWMCCS). The H6000 transferred CINCUSNAVEUR from the first generation of computer systems -- characterized by card decks and single job processing -- to the third generation of multiprogramming, timesharing and terminal input/output. What existed at CINCUSNAVEUR in the way of "computer support" prior to the H6000 was a very "user unfriendly" ANYUK computer which required a great deal of expertise and very specific procedures to operate.

Consequently, when the H6000 was installed, the staff, conditioned by the difficulties of using the prior data processing equipment, was very reluctant to have a computer replace their filing cabinets. After several years of software changes, updates to the Navy WWMCCS Software Standardization System (NWSS) were being passed from the fleet by AUTODIN to the H6000. Messages were not manually manipulated unless they were kicked out of the system because of errors.

In spite of the fact that inputs to the database were being electrically transmitted from AUTODIN to the H6000 before the communication center could distribute the paper copy, the staff, for the most part, avoided the NWSS query

module and held to their filing cabinets. Training sessions given by the software developers on how to use NWSS were not well attended. User reaction to the system was so negative that a separate shop for monitoring the database and correcting the error messages had to be formed using ADP resources. That is, the users who were supposed to be responsible for data content passed the responsibility off to the data processors.

In 1978, a preliminary evaluation of the man-machine interface of the NWSS query module was done by Naval Ocean Systems Center [Ref. 8]. The reason for the study was to investigate the possibility of simplifying the query module since the module, while it is very powerful, is also rather confusing to the infrequent user. There are nonstructured query systems being tested on data bases similar to NWSS -- LADDER, for example -- which would provide the user with a much easier access to the data. LADDER (Language Access to Distributed Data Bases with Error Recovery) will allow a user to ask the computer a question in plain English (Where is the Kennedy?") instead of requiring a specific format and specific command words. The free format LADDER query system has been in test and development status since 1977.

But let's take it a step further. Even if a relatively free format query system was available from NWSS, chances are a good percentage of the staff would still not

be interested -- because it still requires the user to sit in front of a terminal and find characters which are randomly spread over the keyboard. (Would Star Trek ever have been so popular if Captain Kirk had to wheel up to a keyboard and begin typing instead of just facing the panel and speaking into it?) If using the NWSS query module was as easy as loading a tape of voice patterns and "speaking" the query to the computer, would there be less reluctance on the part of the staff and command center team to use the automated data base instead of going to the files?

The problem of C3 today is significantly more complex than at any time in the past. To be competitive in today's automated world, some extension of man's memory and computational abilities is needed. How can this capability be provided without requiring an excessive amount of training? Is it possible to provide a computer tool without requiring typing skills to use it?

The easier it is to access the data, the more likely the staffer will be to use it. The easiest way for a nondata-processor to interface with a computer is simply to talk to it. Consideration for the use of a voice interface with the automated information system would include such questions as:

Is it feasible to utilize a voice recognition system in an environment such as a command center where each member of the watch team could query the computer by voice?

Is it cost effective to train a military member to use a voice recognition system and could it be done in a negligible amount of time?

Would voice input in terms of today's technology be adaptable for female as well as male usage?

What are the tradeoffs in using three, five or ten training passes in terms of training time, error rates and user psychology?

Would it be feasible in terms of system resources to store voice patterns for every member of the watch section on the computer?

Would stress vary the voice patterns to such an extent that the voice input system would be unacceptable in the varying stress situations of the command center environment?

With these thoughts in mind, this thesis investigates the use of a voice recognition system by military operators -- male, female, officer, enlisted -- from technical and non-technical backgrounds.

B. OBJECTIVES

The objective of this thesis was to explore the use of a voice recognition system by a random sample of active duty military personnel. Specifically, to determine the effectiveness of such a system in each of the following three cases:

1. Male Operators versus female operators:

The female voice generally has a higher pitch than the male voice due to the spread of the harmonics in the frequency spectrums of the female. This factor causes problems in frequency resolution and consequently the female voice has been particularly hard for machines to recognize [Ref. 9]. There has been very little work done with female subjects and voice recognition systems. Any system to be used in a command center environment will more than likely have

female as well as male operators. Thus, one of the main objectives of this study was to compare the error rates of the machine using operators of both sexes.

2. Officer operators versus enlisted operators:

Another group of subjects that has had little documented experience with the voice recognition system is that of enlisted personnel. Seemingly, there should be no difference between officer and enlisted. However, this assumption has not been tested. The likely candidate for use of the voice recognition system in the command center environment would be the enlisted member of the watch team. (Hopefully, the ease of use introduced by voice access would change this!) The emphasis in this study was in the use of operational personnel. The intent was to be realistic in the experience levels of the proposed operators in order to provide a true picture of the adaptability of the operators to the equipment and the training required for them to use the equipment.

3. Three, five, or ten training passes to train the voice recognition system:

The accepted algorithm used to train the voice recognition system in this experiment requires ten training passes to "learn" to recognize the operator's utterance. In an extensive vocabulary this can demand a considerable amount of time and can conceivably introduce errors in the training process if boredom and/or fatigue take over. There is an algorithm available to train using five or three utterances as well as ten. The final area examined was the use of three or five training passes vice ten.

II. METHOD

A. DESIGN

Figure 1 shows the conceptual design for this experiment. It is a three-way nested hierarchal analysis of variance. Each of the four groups -- male enlisted, male officer, female enlisted, female officer -- consists of ten subjects. Each subject trained and tested the voice recognition system using three, five and ten training passes in a random order.

B. SUBJECTS

Forty active duty military volunteers participated in this study. There were ten female officers, ten female enlisted, ten male officers and ten male enlisted.

The enlisted subjects were all Navy members stationed at the Naval Postgraduate School. Their ranks ranged from E1 to E8. Their rates were: Religious Program Specialist, Yeoman, Personnelman, Mess Management Specialist, Intelligence Specialist, Data Processor, Storekeeper, Air Intercept Controller, Electronics Technician (including fire control specialist).

The officers were from three U.S. services -- Navy, Army, Air Force -- and the Canadian Forces. They ranged in grade from O3 to O5. All but two were NPS students in the C3, Operations Research, Telecommunications Management,

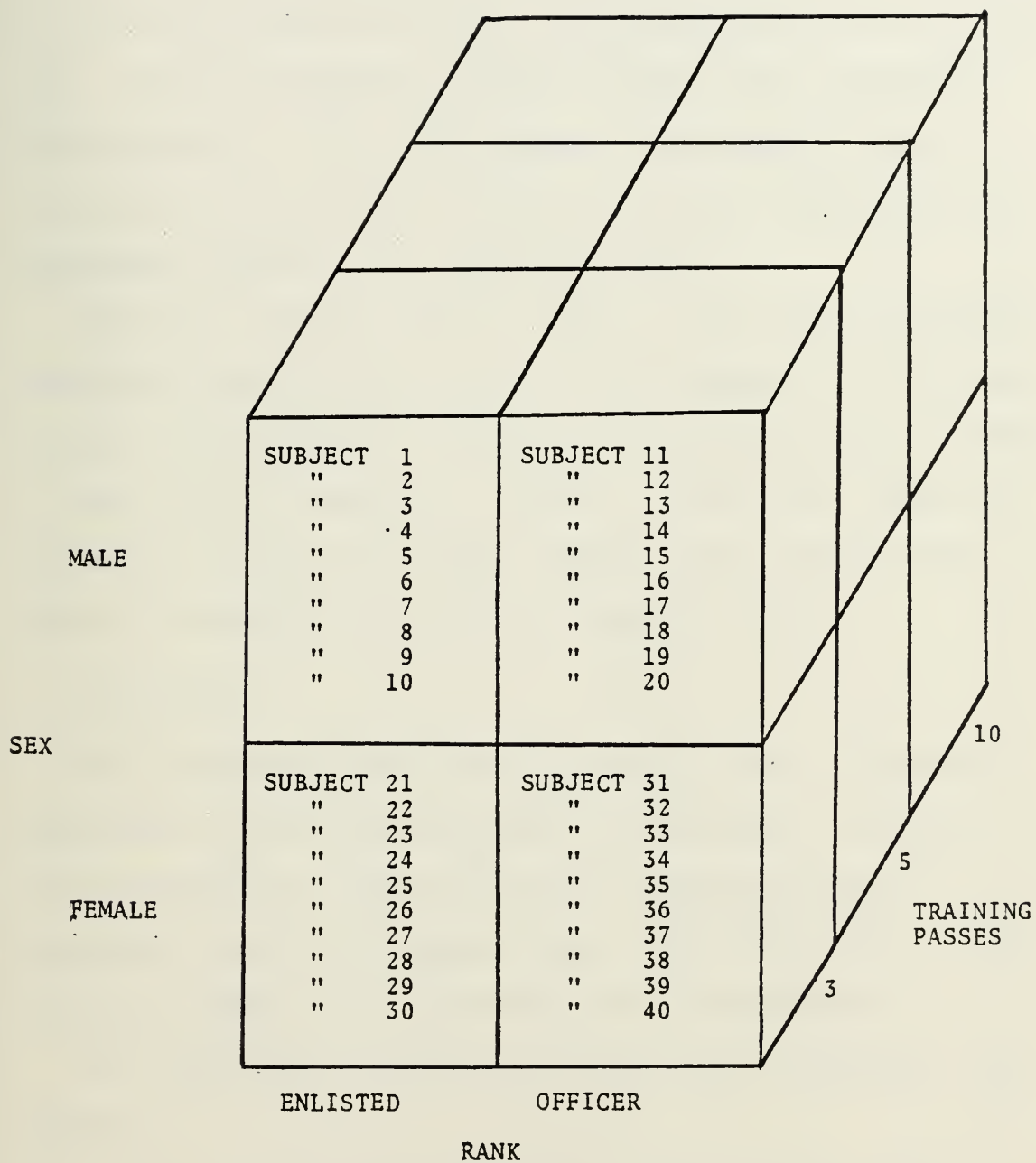


FIGURE 1. CONCEPTUAL DESIGN OF EXPERIMENT

Intelligence, Personnel Management and Communications Engineering curricula. The other two were an Army chemical officer from Fort Ord and an Air Force navigator stationed at the Joint Chiefs of Staff. The backgrounds of the officers were: special warfare, National Oceanic and Atmospheric Administration, ADP, intelligence, telecommunications, cryptology, acquisition, aviator, aerospace engineering, management analysis and communications.

Based on a questionnaire given to each subject before performing the exercise, all but four thought voice input would be easier and less frustrating than typing as a means of input to the computer. Sixteen of the forty subjects had used or seen voice input used but only two had more than an introduction to voice response systems.

C. EQUIPMENT

The equipment used in this research was a Threshold Technology, Incorporated, Model T600 discrete utterance voice recognition system which was located inside an Industrial Acoustic Company sound reduction chamber. The microphone used was a Shure SM10 head microphone.

The Model T600 consists of four basic components (see Figure 2):

- preprocessor unit consisting of an analog speech preprocessor and a digital input/output interface.
- operator console/microphone preamplifier.

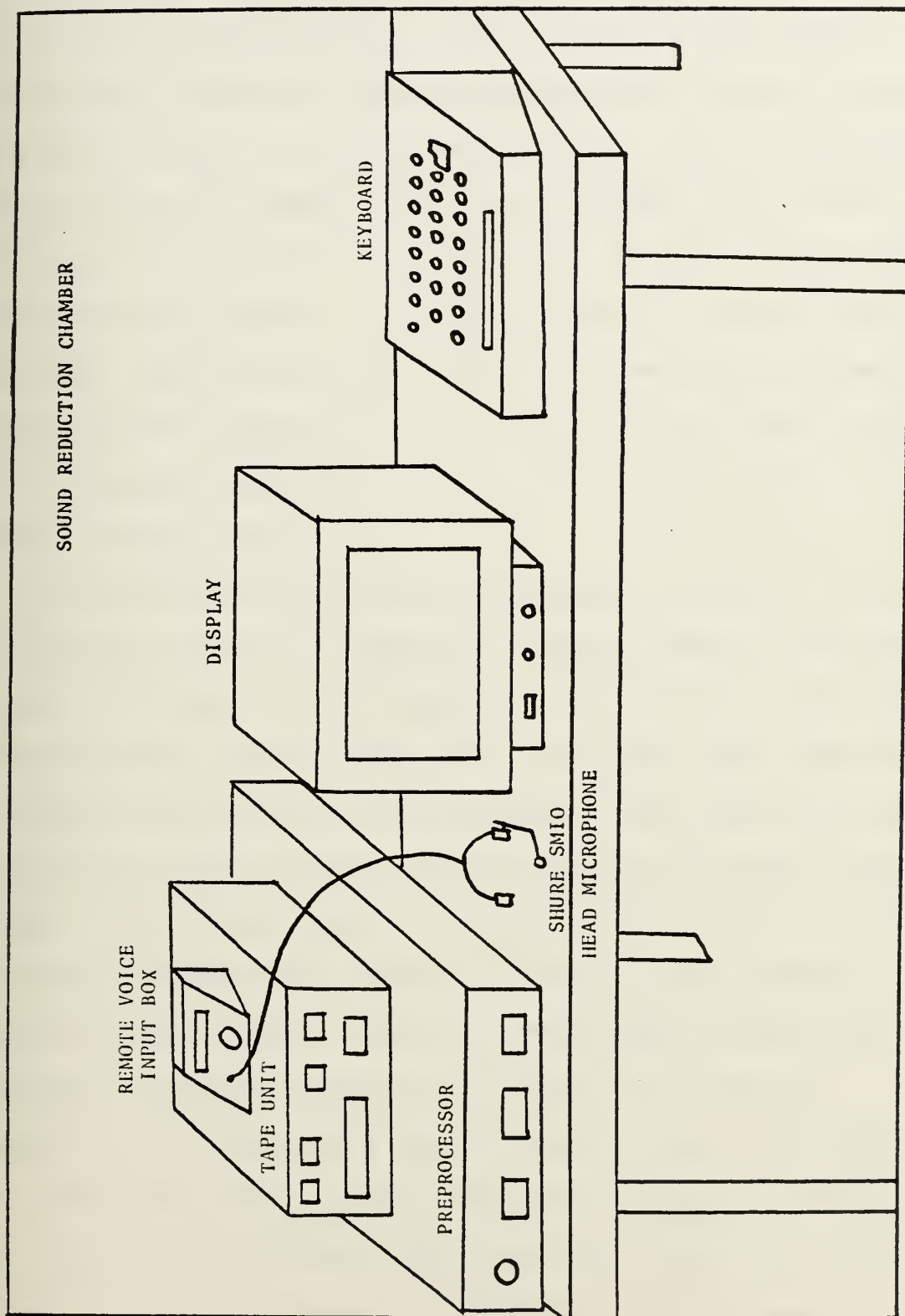


FIGURE 2. EQUIPMENT SET-UP

- tape cartridge unit.
- CRT display and console.

The preprocessor accepts the speech from the microphone preamplifier, extracts speech parameters and converts these to digital signals which are processed by the microcomputer. The microcomputer compares the input signals with stored reference patterns to determine which, if any, of the vocabulary words were spoken. If a close match is found between the input speech pattern and one of the reference patterns, a user defined character string is sent to the user's device via the output interface. If no match is found the system emits a "beep" sound.

The reference patterns are generated during the "training mode" which requires a speaker to repeat several repetitions of each utterance with a variety of inflections as would be used in normal speech. The number of repetitions required is usually ten but for this experiment additional logic was added to the T600 to allow the use of three or five repetitions. An utterance can be a single word ("grid") or group of words ("command and control") lasting from a tenth of a second to two seconds. The only requirement is that the utterance contain no pauses of a tenth of a second or greater. If a tenth of a second pause is made, the T600 will treat the sound as two utterances instead of the intended one. Up to 256 utterances are allowed on this system [Ref. 10].

Each utterance processed by the T600 is passed through nineteen bandpass filters which span the speech spectrum. The overall signal spectral shape is then described using a spectral shape detector which calculates the rate of change of energy level with respect to frequency. The spectral shape and its changes over time are calculated every two milliseconds to determine the presence or absence of thirty-two acoustic features. When the end of the utterance is detected, the duration of the utterance is divided into sixteen time segments and reconstructed into a normalized time base. The T600 extracts a 512-bit feature matrix -- 32 binary features by 16 time features -- for each version of an utterance. Then all matrices (three, five or ten) are combined to produce a single reference matrix for an element.

When an utterance is spoken for recognition by the T600 a 512-bit descriptive matrix is calculated and weighted correlations between this matrix and each reference matrix describing the vocabulary utterances are calculated. The vocabulary with the largest correlation exceeding some preset threshold value is then selected as the utterance spoken. If no correlation exceeds the preset threshold value the T600 emits a "beep" sound [Ref. 11].

The T600 has a magnetic tape cartridge unit which allows the user to build his vocabulary reference patterns and store them on a tape cartridge. When the subject wants to use the

equipment, the tape is loaded into the preprocessor unit. This also allows a user to build a vocabulary for different tasks. He can then load the voice patterns for the task he needs to execute. Since the operator is not dependent on any large computer to store his voice patterns, the equipment can easily be moved and still be operational.

D. PROCEDURE

At the beginning of the session, subjects were given a questionnaire regarding their opinions on voice input versus manual typing. (See Appendix A.) The objectives of the experiment were explained along with an introduction to the voice recognition equipment used and the procedure to be followed. The subject was then seated in a controlled acoustical environment chamber in front of a video display and given instructions on how to train the equipment. (See Appendix B.)

The vocabulary used in this test consisted of fifty utterances -- words and phrases -- varying in length from one to five syllables. The utterances were not chosen to test the machine's ability to distinguish between similar sounds -- "get" and "met," for example. The only consideration in choosing the vocabulary was to have the same number of utterances in each syllable category -- ten one-syllable words, ten two-syllable words, etc. The vocabulary list is shown in Appendix C. Appendix D contains the Confusion Matrix.

Once the subject was introduced to the experiment and equipment, the head mike was mounted and the subject began training the fifty-word vocabulary using either three, five or ten training passes. The number of training passes used first was randomly determined so that each would be used first the same number of times. That is, one-third of the subjects started out using ten training passes. Another third used three training passes first and the last third started out using five training passes.

The training procedure involved repeating an utterance the required number of times and then testing the equipment by repeating the utterance two or three times. If the machine did not respond correctly two out of three times the utterance was retrained. Once the entire vocabulary was trained, the subject tested the equipment by reading through the vocabulary list twice (100 utterances). Any "beeps" or incorrect responses were noted by the experimenter. This entire procedure was repeated using a different number of training passes until each subject had trained and tested the equipment using three, five and ten training repetitions. Subjects were allowed to rest, ask questions, get a drink at any time during the procedure.

E. DEPENDENT VARIABLES

After the training session each subject read through the list of words two times. A record was kept of each time the

machine responded with a "beep" or an incorrect utterance.
A record was also kept of the time each subject took to
complete the experiment.

III. ANALYSIS AND RESULTS

A. HYPOTHESES

The following hypotheses were to be tested:

1. Hypothesis regarding male and female subjects.

H_0 : "There is no difference between male and female users of the voice recognition system."

H_1 : "The null hypothesis is false."

2. Hypothesis regarding officer and enlisted subjects.

H_0 : "There is no difference between officer and enlisted users of the voice recognition system."

H_1 : "The null hypothesis is false."

3. Hypothesis regarding number of training passes.

H_0 : "There is no difference in recognition accuracy when a different number of training passes is used in the voice recognition system."

H_1 : "The null hypothesis is false."

B. RESULTS FOR SEX

The results of this experiment for male and female subjects are shown graphically in Figure 3. The machine's performance for men was slightly better than for women -- 1.8% error rate for men versus 2.1% for women based on twenty subjects making 6000 utterances in each sex category. However, the analysis of variance (ANOVA) results in Table I show an F ratio of .45 which indicates no significant statistical difference in the gender of the operator. Thus the null

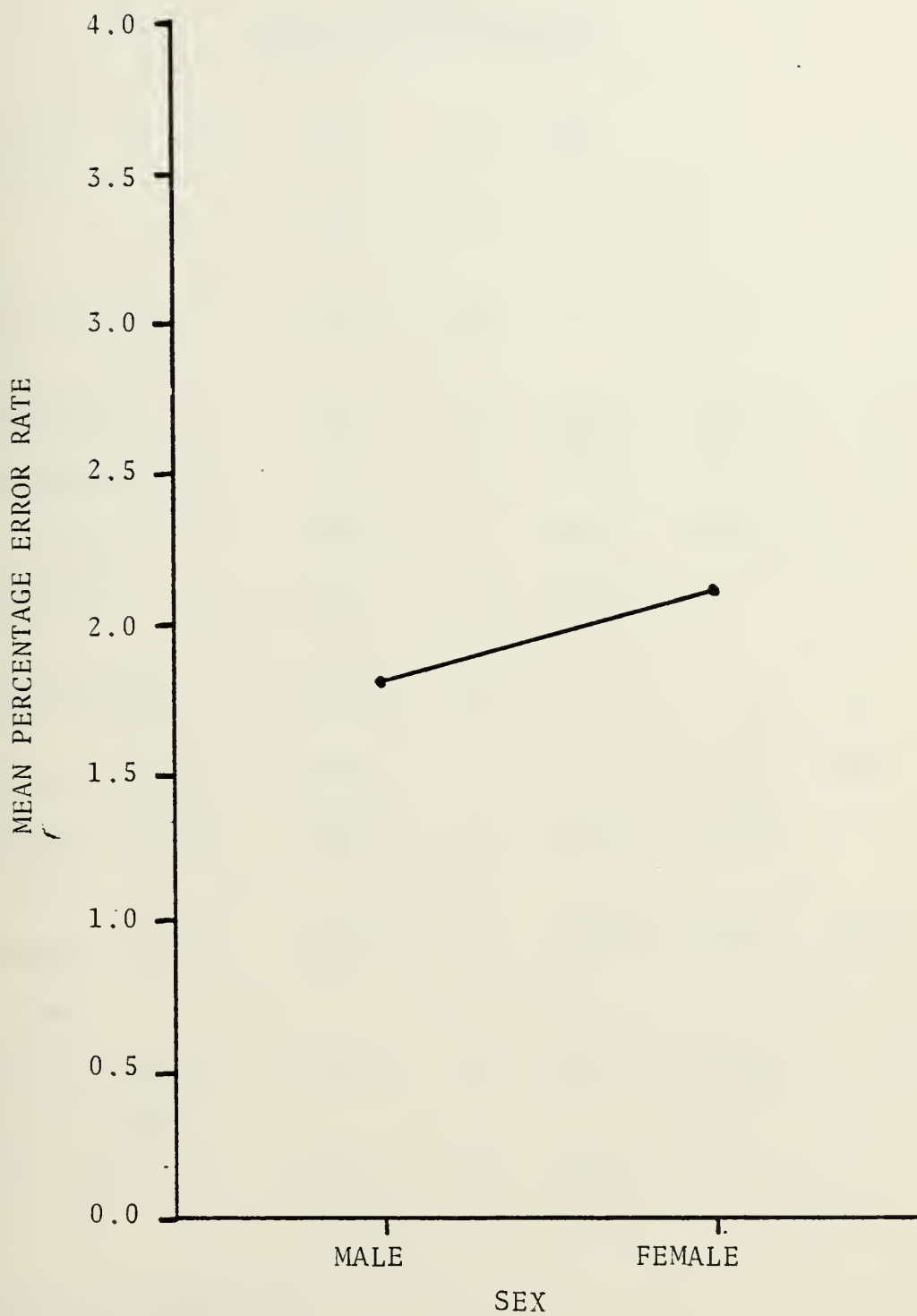


FIGURE 3. ERRORS VS. SEX

TABLE I
ANALYSIS OF VARIANCE

SOURCE	SS	df	MS	F	P
Total	3.1013	119	--	--	
Between Subjects	1.6172	39	--	--	
Male/Female	.0199	1	.0199	.4584	
Enlisted/Officer	.0183	1	.0182	.4217	
Sex x Rank	.0197	1	.0197	.4552	
Error (B)	1.5594	36	.0433		
Within Subjects	1.4841	80	--	--	
Training Passes	.2835	2	.1418	9.1427	.01
Training Passes x Sex	.0330	2	.0165	1.0650	
Training Passes x Rank	.0197	2	.0983	6.3396	.01
Training Passes x Sex x Rank	.0314	2	.0157	1.0129	
Error (W)	1.1165	72	.0155	--	

SS - sum of squares
df - degrees of freedom
MS - mean square
F - F ratio
P - probability of error

hypothesis is not rejected. This result speaks highly for the algorithm used by Threshold. It would appear they have a good handle on the additional requirements needed to process the female voice.

This result further establishes the possibility of using a voice recognition system in a command center environment. The highest probability of error occurred with female subjects but even then the mean percentage error was only 2.1%. That is, out of one hundred utterances (an utterance, again, being a single word or group of words) spoken by a female watch team member to the computer, all but three would be interpreted correctly. If these utterances were being typed, a greater probability of error would exist since one utterance could have as many typing errors as there are characters in the utterance.

C. RESULTS FOR RANK -- OFFICER VS. ENLISTED

Figure 4 shows the comparison of machine errors for the two categories of officer and enlisted. The machine's performance for the enlisted was slightly better than for officers -- 1.85% versus 2.05% mean error percentage based on twenty subjects making 6000 utterances in each rank category.

However, the statistical results from the ANOVA (Table I) show an F ratio of .42. Therefore, there is no significant statistical difference in the error rate of the T600 when

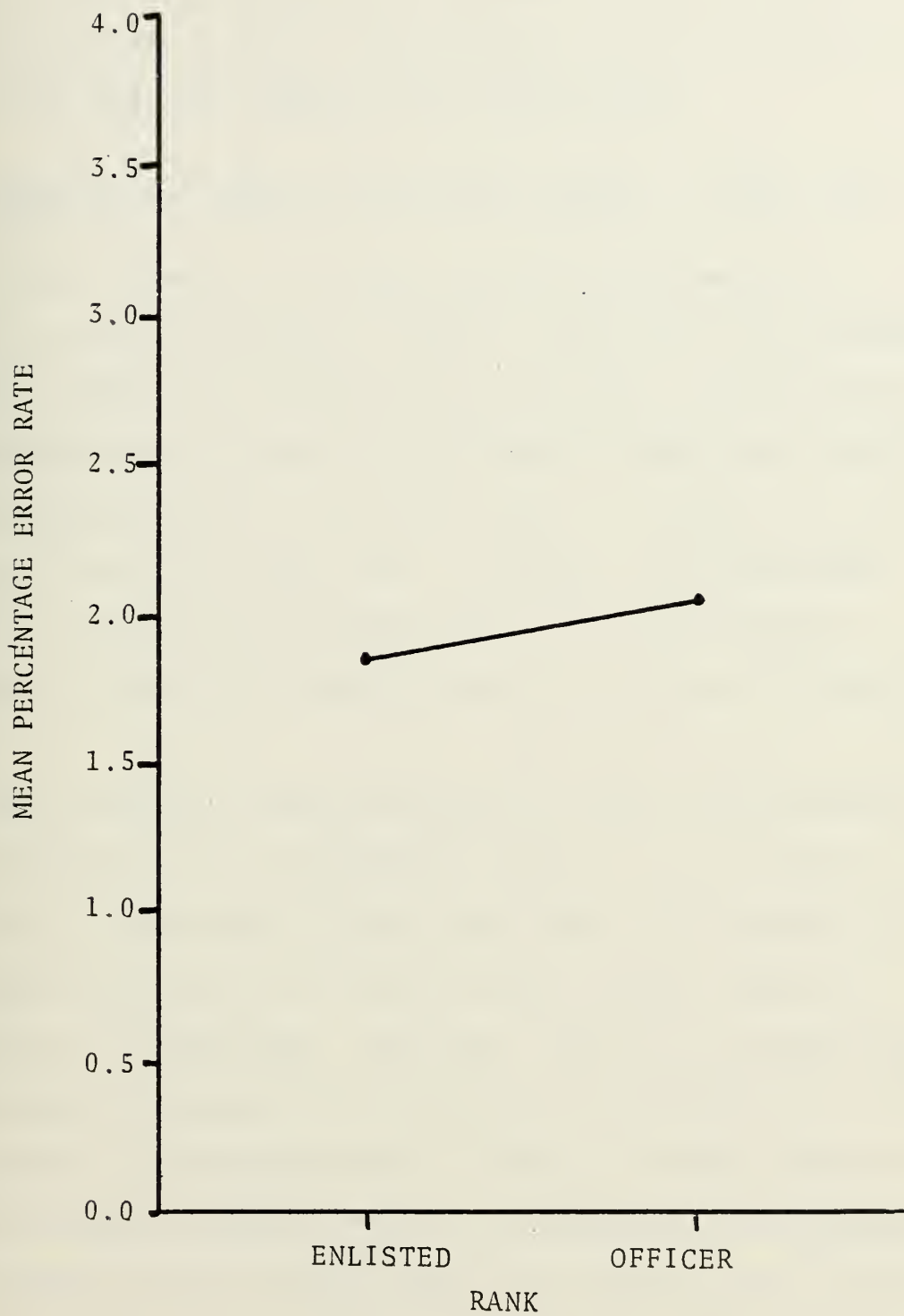


FIGURE 4. ERRORS VS. RANK

used by officer or enlisted personnel. Based on these statistics, the use of a voice system should be favorable to either military member of the watch team.

D. RESULTS FOR NUMBER OF TRAINING PASSES -- THREE, FIVE OR TEN

Figure 5 shows the relationship between number of training passes and rank. Figure 6 shows the relationship between number of training passes and sex. In each case the percentage of error for training the T600 with five or ten training passes is about the same -- around 1% error for both ranks and both sexes. However, the percentage of error using three training passes is significantly higher -- around 2.7% based on rank and 2.4% to 3% based on sex.

This graphical interpretation is proven statistically in the ANOVA with a significance level of .01. That is, the F ratio is 9.14 which is well above the 4.79 required for an alpha level of .01. Based on the F ratio, the null hypothesis is rejected. Therefore, there is a significant difference in recognition accuracy of the T600 when a different number of training passes is used. A Duncan Range test was performed to verify that the difference in performance was between three training passes and five or ten training passes. Five and ten passes had about the same probability of error. Even though three training passes has a

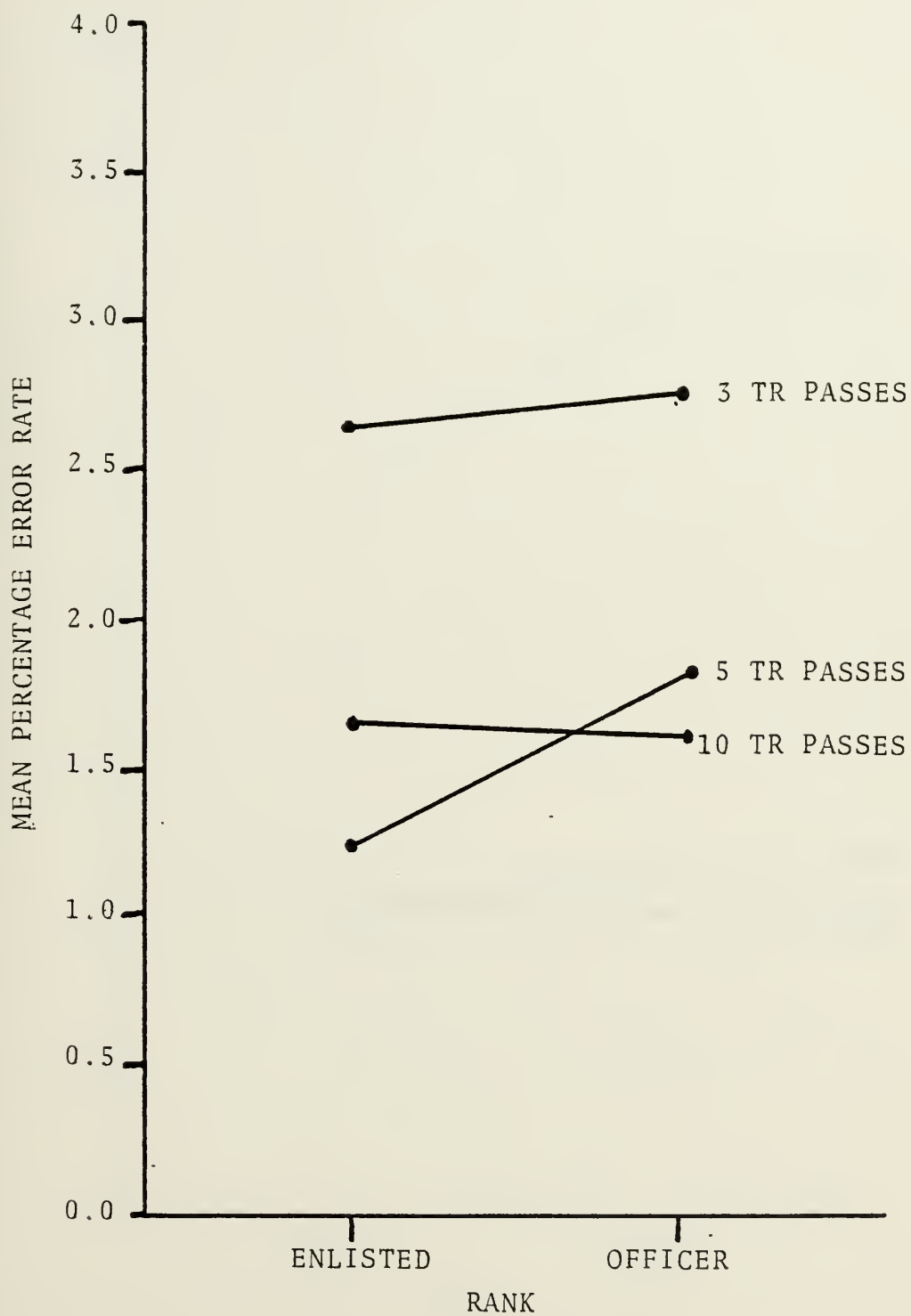


FIGURE 5. NUMBER OF TRAINING PASSES VS. RANK

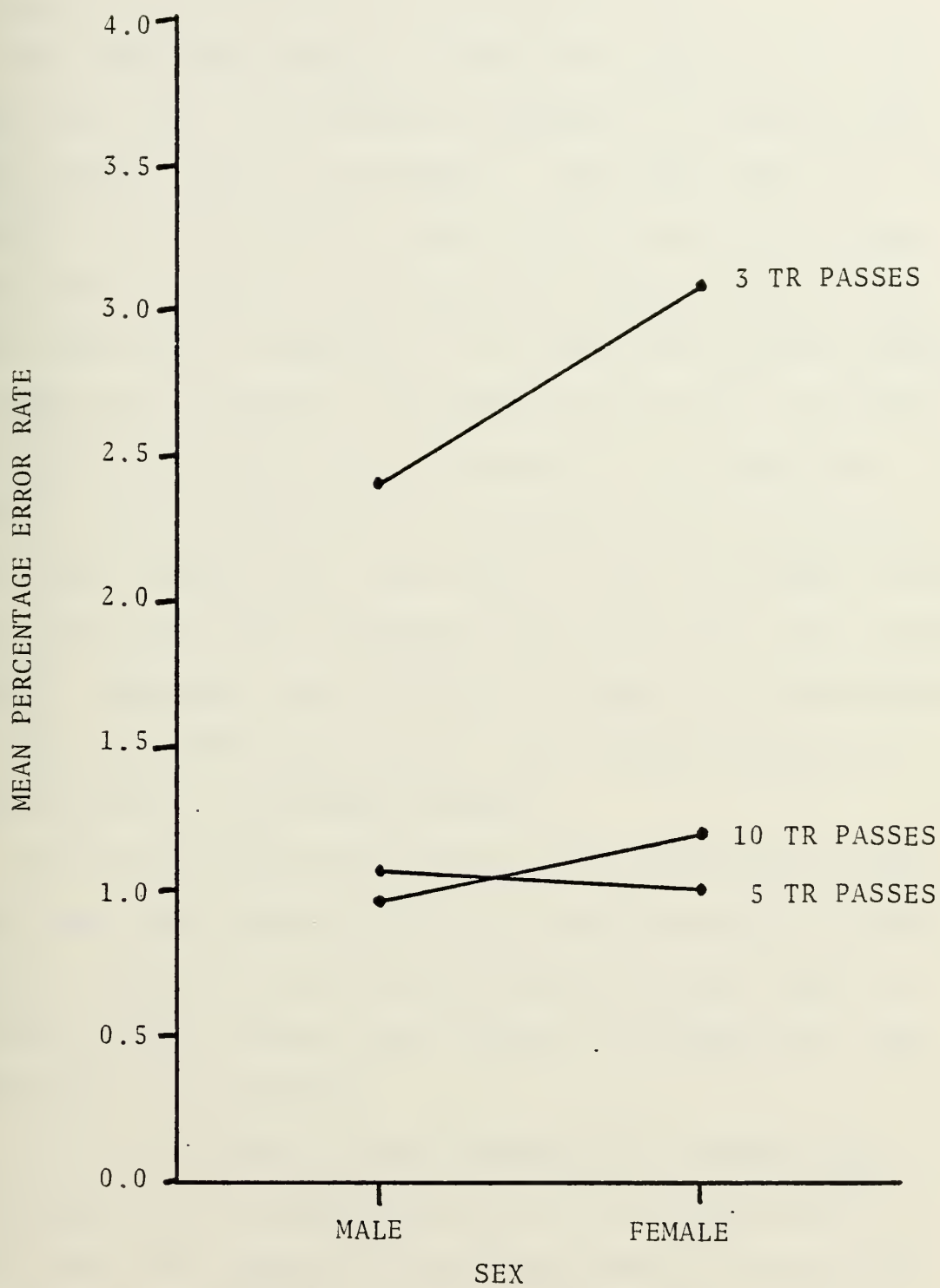


FIGURE 6. NUMBER OF TRAINING PASSES VS. SEX

significantly higher percentage of error over the five and ten passes, it is still only a 3% error rate.

The ANOVA also showed a significant interaction (alpha level less than .01) between the number of training passes used and the rank of the subject. This would imply that an enlisted user would have a lower error rate if he trained the system using five training passes and an officer user would get better recognition if he used ten training passes. A t-test was performed to determine if five and ten passes for officers and five and ten passes for enlisted were indeed different since this interaction seemed unrealistic. The t-test showed both t-statistics (.7682 for women officers and -1.3125 for enlisted women) were within the 95% acceptance region. Therefore, the t-test shows there is no difference in error rate when using five or ten training passes for either officer or enlisted category.

A possible explanation for enlisted performance being lower with ten training passes is that five passes allowed enough variation to build a good identity matrix and ten training passes invited such a degree of boredom that the performance was degraded.

It is interesting to note although the manufacturer recommends ten training passes for the best performance of the system, the results of this study show no significant difference between five and ten training passes. This

result might only apply when a relatively small vocabulary is used but in a crisis situation this could suggest the use of five training passes to get a needed vocabulary on tape quickly. As one's experience with the T600 increases, the use of fewer training passes may be sufficient.

The order in which subjects trained the equipment with the different number of training passes was randomly assigned to prevent any biases in case learning or fatigue factors were involved. Figure 7 shows the percent error rate versus number of training passes used in the order subjects trained. That is, for all subjects who started out the experiment using three training passes, the percent error rate was 2.3%. For all subjects who used five training passes first, the percent error rate was 2%. Those subjects who used three training passes after training with five and ten passes had a percent error rate of 2.9%.

If an improvement due to experience was a factor then five training passes was the only one which demonstrated this. However, the increase in errors as three training passes was used second and third could be due to the fact that subjects became accustomed to putting a lot of inflections in the utterances and when only three passes was used, they ran out of training passes before running out of inflections. The increase in errors when ten training passes was used last could easily be explained as the fatigue

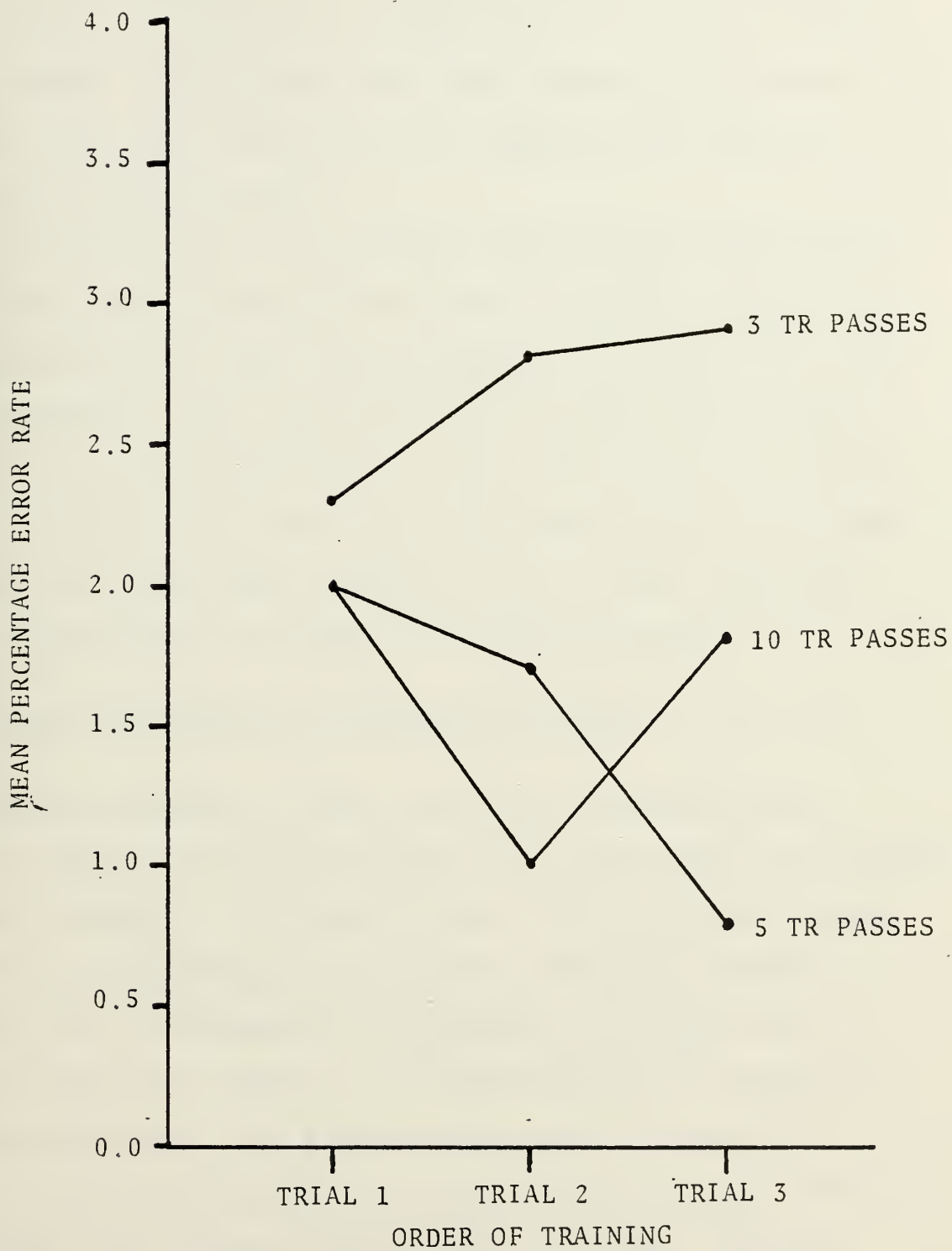


FIGURE 7. NUMBER OF TRAINING PASSES VS. ORDER OF TRAINING

factor. Most subjects took twice as long to train the fifty-word vocabulary using ten training passes as they did using three passes. By the time they were training and testing for the third time the novelty had begun to wear off and voices were getting tired.

A correlation was run on three passes versus five passes, five versus ten and three versus ten to see if a subject who performed well on three training passes did better with five and ten passes. Only the results of the three-five correlation, .67, are significant at .05. The five-ten correlation was .23 and the three-ten correlation was .11. Neither of these is significantly close to 1 or -1 and, therefore, little correlation is evident for these two cases.

E. RESULTS FOR NUMBER OF UTTERANCE SYLLABLES -- 1, 2, 3, 4, 5

Figures 8 through 10 show the error recognition rate for the number of training passes versus the number of syllables in the utterance. In Figure 8, using three training passes, the T600 misinterpreted one-syllable utterances (words 0 through 4 and 25 through 29 in Appendix C) 28 times out of 800 utterances (40 subjects x 10 utterances x 2 repetitions for each utterance) for a percentage error rate of 3.5%.

With one exception the percentage error rate decreased as the number of syllables increased for all three training matrices. This seems reasonable since a greater number of

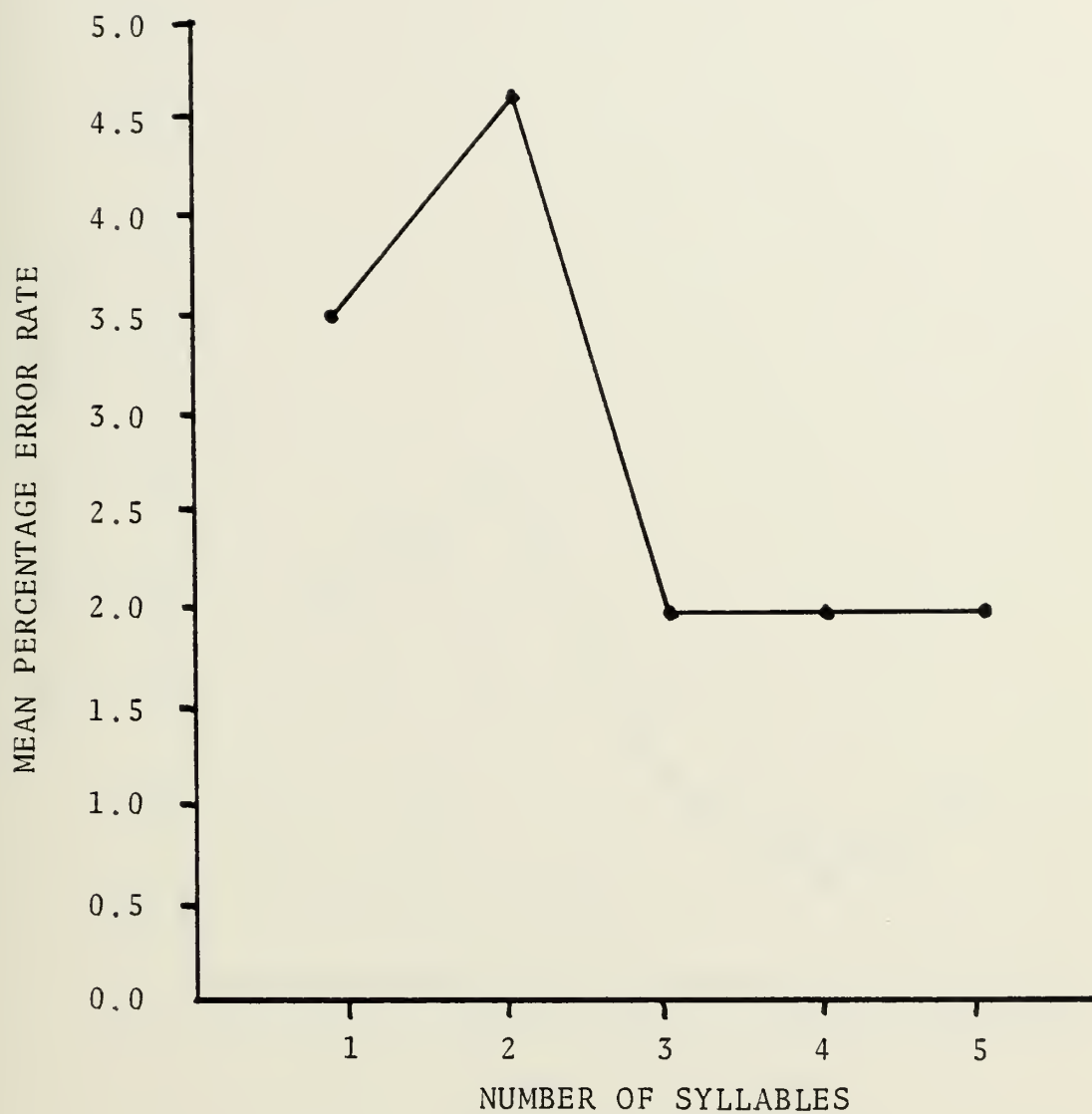


FIGURE 8. ERRORS VS. NUMBER OF SYLLABLES
FOR THREE TRAINING PASSES

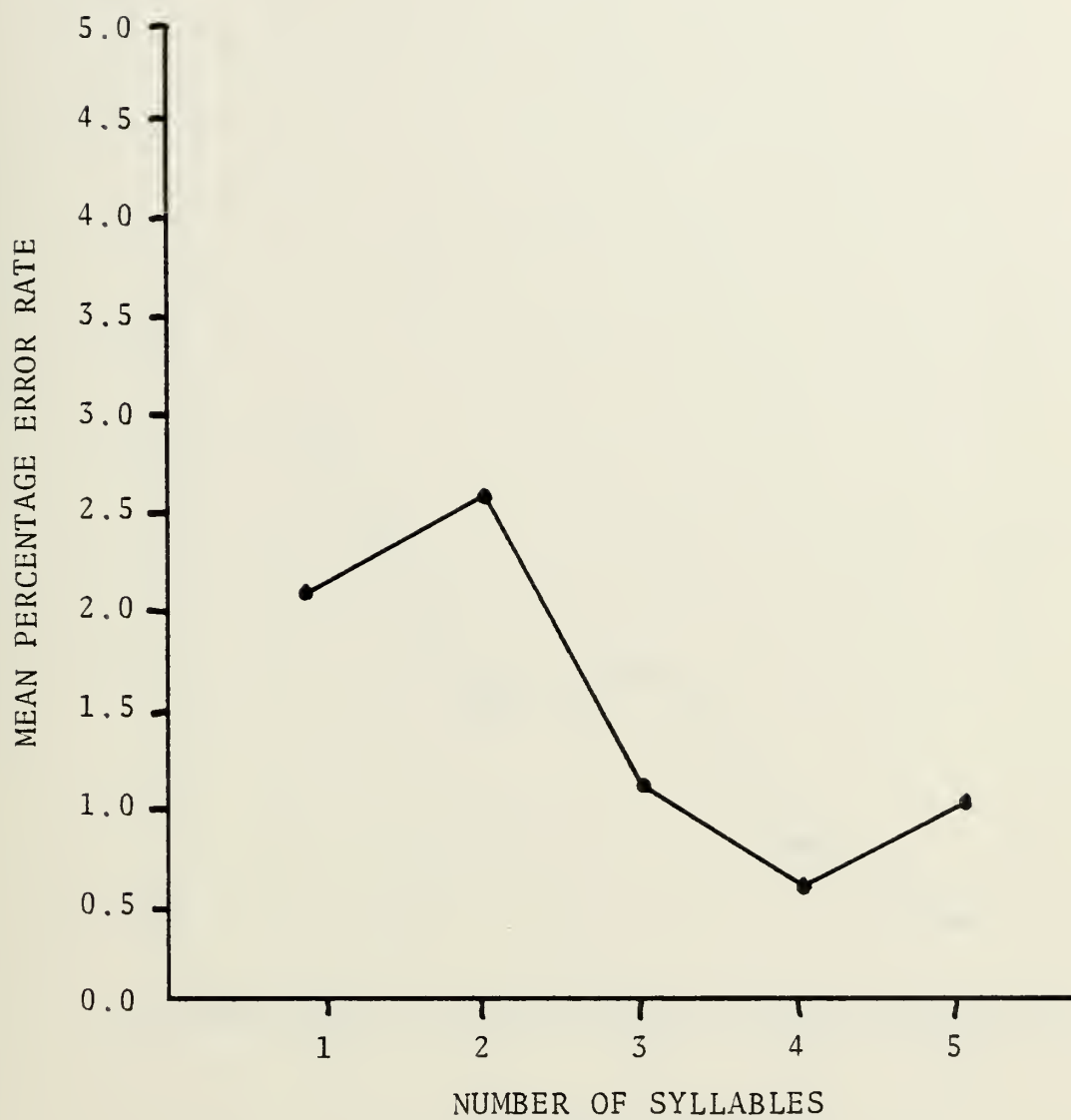


FIGURE 9. ERRORS VS. NUMBER OF SYLLABLES
FOR FIVE TRAINING PASSES

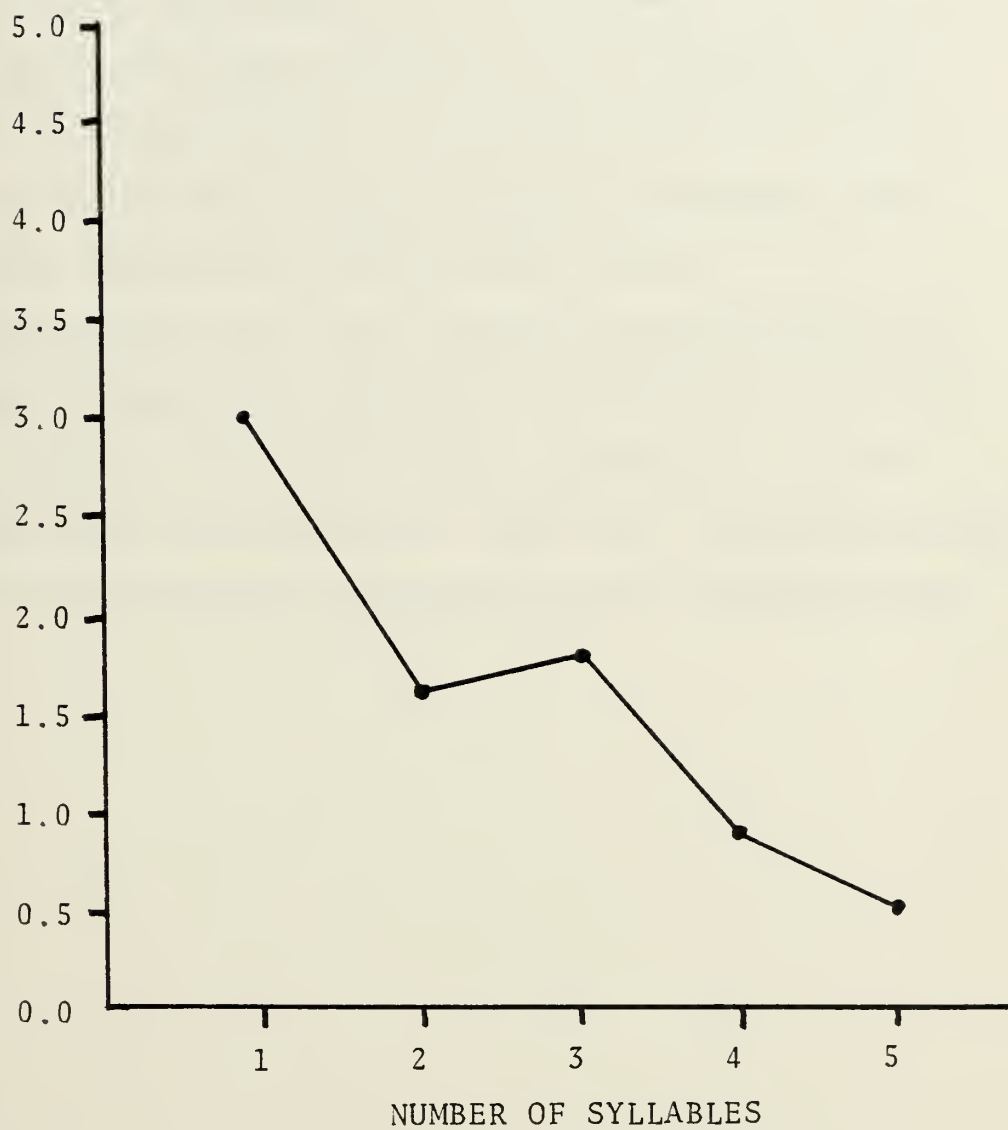


FIGURE 10. ERRORS VS. NUMBER OF SYLLABLES FOR
TEN TRAINING PASSES

syllables give the T600 more unique data to build a recognition matrix for the utterance. The exception for both three and five passes is two syllables. That is, the percentage error rate decreases for utterances from one to five syllables with the exception of two syllables where the error rate is greatest. In the case of ten training passes, the exception is three-syllable utterances, with one syllable having the greatest error rate.

The percentage error rate for five training passes is significantly better than three in all syllable categories. With the exception of two and five syllables it is also better than ten training passes. The best system performance was using five syllable utterances and ten training passes.

IV. DISCUSSION AND CONCLUSIONS

The main points brought out in the previous results section showed that:

1. There was no difference in error rates among the categories of officer and enlisted users of the voice recognition system.
2. There was no difference in error rates among the categories of female and male users of the system.
3. There was a significant difference in error rates of all categories when using three training passes vice five or ten passes but the five and ten training passes had the same error rates.
4. There was significant interaction between rank and the number of training passes used.

Based on these results there should be no problem technically or psychologically with the use of voice recognition systems by military men and women, officer or enlisted. Although this experiment was conducted in a sound reduction chamber, there are two T600 voice recognition systems located in the C3 Laboratory at the Naval Postgraduate School which are frequently in use. The C3 Laboratory simulates the environment of a command center. There have been no problems with background noise in the use of this voice system. Professor R. Elster [Ref. 12] found similar results with his study on The Effects of Certain Background Noises on the Performance of a Voice Recognition System.

The enthusiasm and ease with which the subjects used and trained the equipment are positive signs for the successful use of voice recognition systems in command centers. At the time of this writing, a T600 system has been placed in the command center at Commander in Chief Pacific Fleet (CINCPACFLT). During the week of 1 December 1980, Dr. Gary Pooch and LT Ellen Roland of the Naval Postgraduate School faculty gave a demonstration of the T600 voice recognition system to CINCPACFLT. That staff now has a T600 in the command center which is being experimented with in a variety of areas.

APPENDIX A

SUBJECT QUESTIONNAIRE AND ANSWER SHEET

Please answer the following questions with respect to your capabilities.

For items 3 - 7 designate your feelings from strong feeling for manual input (far left box), no strong feeling either way (middle box), strong feeling for voice input (far right box).

For items 8 and 9, designate your feelings from strong feelings in favor (far right box), no strong feelings either way (middle box), strong feeling against (far left box).

1. Have you ever used voice input?
2. Have you ever seen voice input used?
3. Which might be easier, manual typing input or voice input for communicating with a computer?
4. Would you be more relaxed using manual typing input or voice input?
5. Would you have more flexibility in entering items to a computer with voice input or manual typing input?
6. Would voice input or manual typing allow you more time and freedom to do other things?
7. Would you be more frustrated using voice input or manual typing?

8. In general, do you like the idea of voice input?
9. In general, do you think you would like to use voice input in every day tasks yourself if it were applicable?

TR SEQ

DATE _ _ _ _ _

NAME _ _ _ _ _

RANK/RATE _ _ _ _ _

SUBSPECIALTY _ _ _ _ _

() NPS STUDENT _ _ _ _ _
(CURRICULUM)

() NPS STAFF _ _ _ _ _
(OFFICE TITLE)

() OTHER _ _ _ _ _
(ORGANIZATION & JOB TITLE)

1. YES NO

2. YES NO

MANUAL
TYPING

NEUTRAL

VOICE
INPUT

3. /___/ /___/ /___/ /___/ /___/ /___/ /___/

4. /___/ /___/ /___/ /___/ /___/ /___/ /___/

5. /___/ /___/ /___/ /___/ /___/ /___/ /___/

6. /___/ /___/ /___/ /___/ /___/ /___/ /___/

7. /___/ /___/ /___/ /___/ /___/ /___/ /___/

ABSOLUTELY
NOT

NEUTRAL

ABSOLUTELY
YES

8. /___/ /___/ /___/ /___/ /___/ /___/ /___/

9. /___/ /___/ /___/ /___/ /___/ /___/ /___/

APPENDIX B
INSTRUCTIONS TO SUBJECTS

The fifty-word vocabulary being used with the voice recognizer in the experiment is attached to these instructions. You will be required to repeat each word of this vocabulary three, five and ten times to train the recognizer to recognize your particular patterns of each word. To facilitate recognition by the voice recognizer, you should include in the repetitions as many as possible of the different ways you might say the word in normal speech; for example, use different intonations and emphasis, and small variations in volume.

In order to keep track of the number of times you say each word when using ten repetitions and to reduce breath noise, it is best to speak the ten repetitions in several groups. For example, if the word is zero, it is better to group them as:

000 - 000 - 0000

or

000 - 000 - 000 - 0

rather than

0000000000.

Please observe the following guidelines while inputting voice data to the recognizer.

- Speak each word crisply and quickly but do not overpronounce.
- Leave a distinct pause (specifically, at least one-tenth of a second of silence) between each word so that the recognizer can distinguish the end of one word from the beginning of the next. Do not leave a period of silence within a word or the recognizer will mistake it for two separate words.
- Avoid breathing into the microphone at the end of words as this will generate false inputs to the recognizer.

APPENDIX C

VOCABULARY

WORD #	UTTERANCE	WORD #	UTTERANCE
0	GRID	25	FIRE
1	LAUNCH	26	TIME
2	COURSE	27	MAP
3	GOLF	28	SCOPE
4	SPEED	29	MAINE
5	MESSAGE	30	NEUTRAL
6	ORDERS	31	REFUEL
7	PLATFORM	32	WHISKEY
8	SENSOR	33	LIMA
9	MISSILE	34	LOGOUT
10	SATELLITE	35	TRACK UNKNOWN
11	NEGATIVE	36	LONGITUDE
12	SUBMARINE	37	TORPEDO
13	ENEMY	38	BLUE FORCE ONE
14	EXECUTE	39	ROMEO
15	SAN FRANCISCO	40	FLIGHT CONTROLLER
16	HUMAN FACTORS	41	SEA OF JAPAN
17	UNITED STATES	42	HONOLULU
18	CLOSE OUT CHARLIE	43	ADVANTAGES
19	COLORADO	44	CONTINUOUS
20	CONNECT TO CHARLIE	45	TASK FORCE COMMANDER
21	NORTH ATLANTIC MAP	46	NORTH CAROLINA
22	COMMAND AND CONTROL	47	BEARING AND DISTANCE
23	CONTINUOUS SPEECH	48	PLOT ALL SUBMARINES
24	VOICE TECHNOLOGY	49	UNITED AIR LINES

APPENDIX D
CONFUSION MATRIX

Out of 240 utterances, each word on the left side was interpreted by the T600 as the word in the row with a number. The last column, beep, indicates the number of times the T600 rejected the utterance and beeped. Raw numbers were used because roundoff errors made percentage values insignificant.

[illegible]

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